An Account of Geographic Concentration Patterns in Europe*

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Abstract

Using entropy indices and associated bootstrap tests, we describe the distribution of economic sectors across Western European regions over the 1975-2000 period. We decompose geographic concentration into its within-country and between-country components. In addition, we estimate centre-periphery gradients in sectoral location patterns and the impact of EU membership on countries' internal geography. It is found that manufacturing has become gradually more concentrated, although the locational bias towards central regions has become weaker. Conversely, market services have been relocating towards centrally located regions. EU integration appears to have strengthened countries' internal concentration trends.

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<All tables and figures at end>

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1 Introduction

The spatial analysis of integrating market economies has recently regained prominence on the economic research agenda. This has two main reasons. First, as policy initiatives and technological advances have conspired over the last half-century to reduce the costs of economic transactions across region and country borders, economic activities are generally believed to have become increasingly "footloose". Second, theorists have made substantial progress in the 1990s in modelling location forces that are not due to underlying spatial heterogeneity but to the interplay between market forces and distance costs in homogeneous space. The "new economic geography" provides a formal treatment of agglomeration and dispersion forces in such a world.[1] One of the most interesting insights of this literature is that economic integration may render some activities less rather than more "footloose", because falling trade costs can contribute to a strengthening of agglomeration economies.

Both the policy-related and the theory-based motivations for renewed interest in spatial economics are particularly relevant to Western Europe, which has gone through a process of unprecedented economic integration, and where underlying endowment differences are small compared to more resource-dependent world regions. Considerable research effort has therefore been expended on studying location patterns of sectoral production and employment in Europe.[2] It has proven difficult to distil strong stylised facts from this research. One reason for the heterogeneity of results is that the studies differ quite strongly in the data and measures they employ. More fundamentally, it appears that sectoral relocation in Europe is a slow and multifaceted process that does not leap out from the data. Overman, Redding and Venables (2001) have summarised the dominant view as follows: "In contrast to the US, EU countries are becoming increasingly specialised (...), although the changes are not particularly large." This diagnosed tendency towards increased specialisation applies to the distribution of manufacturing sectors across countries - little is still known about geographic concentration of sectors at sub-national level and across the full range of economic activities.

The aim of this paper is to provide a comprehensive account of sectoral concentration patterns across Western European regions, in a quest for empirically well-founded stylised facts. Our study distinguishes itself from the existing literature in four principal respects.

First, we apply entropy indices to measure geographic concentration. These

[1] See Fujita, Krugman and Venables (1999) and Fujita and Thisse (2002) for comprehensive statements.

[2] For studies of geographic concentration patterns in Europe using sectoral output or employment data, see Aiginger and Leitner (2002), Aiginger and Pfaffermayr (2003), Amiti (1999); Brülhart (2001a, 2001b); Clark and van Wincoop (2001); Haaland, Kind, Midelfart Knarvik and Torstensson (1999); Hallet (2000); Helg, Manasse, Monacelli and Rovelli (1995); Imbs and Wacziarg (2003); Kalemli-Ozcan, Sorensen and Yosha (2003); Krugman (1991); Midelfart Knarvik, Overman, Redding and Venables (2000); Peri (1998); and Storper, Chen and De Paolis (2002).

indices have distinct advantages over the conventional measures in this literature. Entropy measures are known for their suitability to inequality decomposition analysis. This allows us to compare within-country concentration to between-country concentration in conceptually rigorous fashion. Furthermore, we can quantify how much each sector contributes to aggregate geographic concentration, by decomposing aggregate entropy into the "factor contributions" of individual sectors. We compute these measures separately for "relative concentration", where we measure the degree to which sectors are concentrated relative to the geographic distribution of aggregate activity, and for "topographic concentration", where we measure the degree to which sectors are concentrated in physical space.

Second, we employ bootstrap inference to test the statistical significance of changes in observed concentration measures. These tests have been shown to be particularly accurate when used in conjunction with entropy measures.

Third, we use regression techniques to estimate (a) the degree to which sectoral location patterns are influenced by the centrality and peripherality of regions and (b) whether and to what extent accession to the EU has affected the time profiles of within-country location patterns.

Fourth, our study is based on comprehensive regionally and sectorally disaggregated data sets. Our main data set provides us with a balanced panel of employment in eight economic sectors in 236 NUTS-2 and NUTS-3 regions belonging to 17 Western European countries over the 1975-2000 period.[3] The eight sectors of this data set cover the full range of economic activities, including agriculture and services. Through the use of employment as the size measure we can avoid problems of currency conversion inherent in value data. As a complement to the main data set, we use a data set that disaggregates manufacturing value added into nine industries for 116 EU-15 NUTS-1 and NUTS-2 regions over the 1980-1995 period.

We have several motivations for studying the relative magnitude of intra- and international specialisation trends. One motivation stems from the fact that this distinction has considerable policy relevance. For example, the desirability for a country to adopt the single currency hinges on the degree of country specificity of economic shocks. To the extent that shocks are sector specific, inter-country specialisation will increase the asymmetry of shocks and thereby reduce the attractiveness of monetary union. If specialisation were mainly an intra-country phenomenon, however, it would be of no consequence for the cost of monetary union. Second, there is an ongoing debate about the extent to which regional policy should fall in the remit of national governments or in that of supranational European Union authorities. To the extent that regional policy targets certain sectors or that specialisation patterns affect relative income levels, inter-country specialisation will strengthen the case for delegating regional policy to a supranational authority, while intra-country

[3]NUTS (Nomenclature of Territorial Units for Statistics) is Eurostat's classfication of sub-national spatial units, where NUTS-0 corresponds to the country level and increasing numbers indicate increasing levels of sub-national disaggregation.

specialisation is arguably better addressed by national policy makers.[4]

Another motivation for our empirical study is that the available theoretical apparatus yields no consensus prediction. As we discuss below, the standard neoclassical model predicts relatively stronger *inter*national concentration, while in the canonical "new economic geography" framework *intra*national concentration is more likely to dominate. Relative specialisation trends at different levels of spatial aggregation can therefore serve as an informal test of theoretical paradigms.

Our paper is organised as follows. Section 2 presents the measures used, their associated bootstrap tests and data resources. In Section 3, we describe geographic concentration patterns using the entropy measures, and in Section 4 we apply regression techniques to estimate locational centre-periphery gradients and the impact of EU accession. A selective discussion of our empirical findings against the background of relevant trade and location theory is provided in Section 5. Section 6 concludes.

2 Measurement, inference and data

2.1 Additively decomposable inequality measures: General entropy

Since Krugman (1991), "locational Gini indices" have become the measure of choice for studies of geographic specialisation patterns. The Gini index has strong intuitive and pedagogical appeal, but it is not ideally suited to our analysis. One feature that we seek in a measure of geographic concentration is decomposability into its within-country and between-country components. The Gini index is only decomposable if the range of the values taken by the variable of interest does not overlap across subgroups of individual observations (Cowell, 1980). This is evidently not the case in our context: regions in different countries may well have similar degrees of specialisation in a particular sector. We therefore use measures that pertain to the single-parameter generalised entropy class (GE(α)). Entropy measures have the welcome feature of being additively decomposable both by population subgroup and by factor components. In addition, entropy measures lend themselves particularly well to bootstrap-based statistical inference.[5]

[4] Giannetti (2002) has found that the sectoral composition of EU regions affects those regions' growth trajectories and thus helps explain the coexistence of inter-country income convergence and intra-country income divergence. Also note that one criterion for "objective 2" status and the associated eligibility for regional aid from the EU, is a higher percentage of jobs in industry than the EU average and a decline in industrial employment.

[5] We have computed Gini indices as well as entropy measures, where applicable. The choice of index did not affect our qualitative findings, and we therefore report only the entropy-based results. The results are available from the authors on request.

The underlying concepts are as follows. We consider a population of *basic units* $i \in \{1, 2, ..., N\}$, where each basic unit is associated with a unique value of the measured variable y, and $\sum_{i=1}^{N} y_i \equiv Y$. Then, we define an exhaustive partition of this population into mutually exclusive *subgroups* of basic units $k \in \{1, 2, ..., K\}$. Moreover, the variable y is defined such that it can be subdivided exhaustively into mutually exclusive *factors* $f \in \{1, 2, ..., F\}$.[6]

Members of the generalised entropy (GE) class of inequality indices are defined by the following expression:

$$GE(\alpha) = \frac{1}{\alpha^2 - \alpha} \left[\frac{1}{N} \sum_{i=1}^{N} \left(\frac{y_i}{\overline{y}} \right)^{\alpha} - 1 \right] \tag{1}$$

where

$$\overline{y} = \frac{1}{N} \sum_{i=1}^{N} y_i = \frac{Y}{N},$$

and α is a sensitivity parameter. α measures the weight given to distances among values taken by y at different parts of the distribution of y. It can in principle be set to any real number. The neutral parameter value is 1. If $\alpha < 1$, then a bigger weight is attributed to the dispersion of y in the lower tail of the distribution of y over i, and if $\alpha > 1$, then a bigger weight is attributed to the dispersion in the upper tail. Like the Gini, these indices increase in the degree of inequality.

Following standard practice, we confine our analysis to the cases where $\alpha = 1$ and $\alpha = 2$. Using L'Hopital's rule on equation (1), the first case yields the *Theil index* of inequality:[7]

$$GE(1) = \frac{1}{N} \sum_{i=1}^{N} \frac{y_i}{\overline{y}} \log \frac{y_i}{\overline{y}}, \tag{2}$$

where

$$0 \leq GE(1) \leq \log N.$$

The second case yields *half the squared coefficient of variation*, CV:

$$GE(2) = \frac{1}{2} CV^2, \tag{3}$$

where

$$CV = \frac{1}{\overline{y}} \left[\frac{1}{N} \sum_{i=1}^{N} (y_i - \overline{y})^2 \right]^{\frac{1}{2}},$$

[6] In the income distribution literature, where these measures were first used by economists, i would typically refer to individuals, y to income, k to socio-economic categories and f to different income sources (wages, government transfers, capital income, etc.). The definitions of these concepts in the context of our study will be provided below.

[7] For a previous application of the Theil index to geographic concentration see Aiginger and Davies (2000), who applied the index to country-level output data for the EU. They did not make use of the index's decomposability.

and

$$0 \leq GE(2) \leq \frac{1}{2}(N-1).$$

These indices are **decomposable by population subgroups** in particularly appealing fashion. Each GE index can be decomposed additively as:

$$GE(\alpha) = GE_w(\alpha) + GE_b(\alpha), \tag{4}$$

where GE_w and GE_b stand for within-subgroups and between-subgroups general entropy respectively.

Between-group inequality, GE_b, is computed by applying equation (1) to the K subgroup means $\overline{y}_k$ instead of the N observations on y.

The contribution of within-subgroup inequality is computed as follows:

$$GE_w(\alpha) = \sum_{k=1}^{K} \left(\frac{N_k}{N}\right)^{1-\alpha} \left(\frac{Y_k}{Y}\right)^{\alpha} GE_k(\alpha), \tag{5}$$

where $GE_k(\alpha)$ is the GE index as defined by equation (1) but confined to observations belonging to subgroup k (so that N becomes N_k). Subgroup GE indices are therefore calculated as if each subgroup were a separate population.

It is evident from equation (5) that the GE(1) index weights subgroup inequalities by the y shares. The GE(2) index decomposition implies weights that are based on the n shares as well as the y shares. For decompositions by population subgroups, GE(1) is generally preferred to GE(2), because for GE(2) the weights used to compute GE_w are not independent from GE_b.[8]

For a **decomposition of overall inequality by factors**, we seek a rule according to which we can express a measure of total inequality in y, which we denote I, as the sum of the contributions from all factors, so that factor f provides a disequalising contribution if $S_f > 0$, and an equalising contribution if $S_f < 0$:

$$I = \sum_{f=1}^{F} S_f(I).$$

Functions that generate suitable values of factor contributions S_f are referred to as "decomposition rules". The adoption of such a rule is necessary to apportion inequality contributions exhaustively and uniquely to individual factors when the y-contributions from different factors are correlated. In general, there is an infinite possible number of such rules, and the choice is arbitrary. However, Shorrocks

[8] Bourguignon (1979) and Shorrocks (1980) have proven that GE(0) and GE(1) are the only additively decomposable scale invariant inequality measures for which the weigths of the within-subgroup inequalities sum to a constant (i.e. 1) and are independent of GE_b. Shorrocks (1984) showed that even if one relaxes the *additively* decomposable constraint by allowing weaker aggregation properties, the admissible set of indices expands only to monotonic transformations of the $GE(\alpha)$ family.

(1982) has proven that under some weak and plausible assumptions one arrives at the following unique decomposition rule for proportional factor contributions $s_f(I)$:

$$s_f(I) = \frac{S_f(I)}{I} = \rho_f * \frac{\sigma(\mathbf{y}_f)}{\sigma(\mathbf{y})} = \frac{\mathrm{cov}(\mathbf{y}_f, \mathbf{y})}{\sigma^2(\mathbf{y})},$$

where $\mathbf{y} = (y_1, ..., y_N)$ is the vector of total y's, $\mathbf{y}_f = (y_{f1}, ..., y_{fN})$ is the vector of y's from factor f, σ is the standard deviation, and ρ_f is the correlation between $\mathbf{y}_f$ and $\mathbf{y}$.[9] This decomposition rule is especially appealing, since, as shown by Shorrocks (1982), it yields the same set of proportional factor contributions s_f irrespective of the inequality index I that is chosen. In terms of the proportional factor contributions, the choice of inequality measure therefore becomes irrelevant. However, it is standard practice to resort in this context to the GE(2) index, for which the Shorrocks decomposition rule happens to be the "natural rule", since:

$$s_f = \rho_f \frac{\overline{y_f}}{\overline{y}} \sqrt{\frac{GE(2)_f}{GE(2)}}. \tag{6}$$

Hence, a certain factor f's proportional contribution to total inequality is the product of (a) the correlation of $\mathbf{y}_f$ with $\mathbf{y}$, (b) f's share in total y, and (c) the inequality in that factor relative to total inequality, measured using GE(2).[10]

2.2 The spatial aggregation problem: Topographic versus relative concentration

In the income distribution context, the definition of a "basic unit" is straightforward: each person is a basic unit. Applied to our study, the definition of basic unit is less obvious. Our most disaggregated data pertain to NUTS-2 regions, i.e. subnational spatial units of European countries.[11] There are significant differences among those regions, in terms of both geographic and economic size. It is well known that spatial inequality measures are sensitive to the definition of regions. This is commonly referred to as the "modifiable areal unit problem" (MAUP), according to which the results of statistical analysis of data for spatial zones can be varied at will by changing the zonal boundaries (Arbia, 1989). The problem has two components; a problem of scale, involving the aggregation of smaller units into larger ones, and a problem of alternative allocations of component spatial units to zones (gerrymandering).

[9] s_f, of course, corresponds to the slope coefficient from a regression of $\mathbf{y}_f$ on $\mathbf{y}$.

[10] S_f can be interpreted in two different ways; (a) as the inequality that would be observed if factor f were the only source of inequality in y, S_f^A, and (b) as the amount by which total inequality would change if inequality in terms of factor f were reduced to zero, S_f^B. Shorrocks (1982) has shown that, for the GE(2) index, $S_f = \frac{1}{2}(S_f^A + S_f^B)$, whereas for most other inequality indices there exists no such obvious connection between S_f and (S_f^A, S_f^B).

[11] There are some countries for which we do not have regional data (see Appendix 1). For Sweden, the data are at NUTS-3 level.

The only way of measuring spatial inequality without confronting the MAUP would be by collecting data at the level of basic units. We will work with two conceptions of a basic unit; a square kilometre and an employed person. This choice of definition may seem innocuous, but in fact it implies fundamentally different underlying meanings of "geographic concentration". Our results show that empirical results are highly sensitive to this choice.

When we define a basic unit as a square kilometre (or any other areal unit), the no-concentration benchmark obtains where an activity is spread perfectly evenly across geographic space. Conversely, any departure from such an even spatial spread will register as geographic concentration, irrespective of the spatial distribution of endowments or of other economic sectors. We refer to this conception of geographic concentration as "*topographic concentration*".[12]

If we use the alternative definition of a basic unit as "an employed person", then we condition topographic space by the distribution of overall employment. In this case, the no-concentration benchmark implies that each (co-located group of X) employed person(s) allocates her (their) working time across sectors exactly according to the proportions corresponding to those sectors' use of employed labour across all locations. This is the concept of concentration that has been used in most previous studies and that seems economically most relevant. We shall refer to this definition as "*relative concentration*". Hence, given the spatially uneven distribution of aggregate employment, a sector that happens to be perfectly evenly spread in space would have zero topographic concentration but positive relative concentration. Conversely, a sector that is spread exactly proportionally to total activity would have zero relative concentration but positive topographic concentration. Where we calculate relative concentration using value added rather than employment data, we condition space on the distribution of overall value added. In this case, a basic unit corresponds to one unit of value added, irrespective of the sector that generates that unit. Note, finally, that we use the expression "geographic concentration" as the general term that encompasses both the "topographic" and the "relative" definition.

Our observed regions $r \in \{1, 2, ..., R\}$, are sets of basic units i, and we refer to them as *observed units*.[13] The size of each observed unit is defined in terms of the number of basic units it contains, n_r, such that $\sum\limits_r n_r = N$. The observed variable Y_r corresponds to observed-unit totals of unobserved basic-unit realisations of y ($Y_r = \sum\limits_i y_{ir}$). Finally, we set countries to be our subgroups k, so that $N > R > K$.

In this setting, the expressions for the two basic entropy indices become:

[12] Note that this definition differs from the concept of "absolute" concentration, where basic units are defined as corresponding exactly to the observed spatial units, i.e. regions or countries (Aiginger and Leitner, 2002; Aiginger and Pfaffermayr, 2003; Haaland *et al.*, 1999). As pointed out by Combes and Overman (2003), the no-concentration benchmark implied by "absolute" concentration is that an industry has identical employment/output in all regions irrespective of those regions' size, which is difficult to reconcile with any market-based location model.

[13] In the income distribution context, r could for instance correspond to households.

$$GE(1) = \sum_{r=1}^{R} \frac{n_r}{N} \frac{\overline{y}_r}{\overline{y}} \log \frac{\overline{y}_r}{\overline{y}} = \sum_{r=1}^{R} \frac{Y_r}{Y} \log \frac{\overline{y}_r}{\overline{y}}, \quad (7)$$

and:

$$CV = \frac{1}{\overline{y}} \left[\sum_{r=1}^{R} \frac{n_r}{N} \left(\overline{y}_r - \overline{y} \right)^2 \right]^{\frac{1}{2}}, \quad (8)$$

where

$$\overline{y}_r = \frac{Y_r}{n_r}, \text{ and } \overline{y} = \frac{Y}{N},$$

and where n_r corresponds to regions' total employment, value added or land area.

These measures are true representations of actual inequality only if inequality among basic units inside observed units is zero. If intra-regional inequality exists, which of course applies in reality, the weighted measures will underestimate total inequality. This downward bias in measured inequality rises with the level of spatial aggregation. It is a manifestation of the scale-related MAUP. By size-weighting the GE indices in expressions (7) and (8), we minimise the downward bias given the data at hand, but we cannot eliminate it.[14]

For the second component of the MAUP, the arbitrariness inherent in administrative region borders, given a certain distribution of region sizes, there is no methodological palliative. In addition, broad statistical definitions of sectors may also obscure economically relevant concentration patterns, if offsetting concentration structures of sub-sectors are blurred by the aggregation of those sub-sectors. Absolute levels of the indices, and decompositions thereof, must therefore be interpreted with caution. However, the focus of this study is on changes in geographic concentration patterns over time, and if biases due to the MAUP and to sectoral aggregation are stable intertemporally, their absolute magnitude will not distort our inference.[15]

[14] One approach used in the income inequality literature to deal with grouped data is to estimate a certain distribution function parametrically using maximum likelihood, and to calculte inequality indices over the estimated distribution. We do not follow this route for two reasons. First, we have no priors as to the functional form of such a distribution. Second, there is no clear case based on empirical work for favouring either our non-parmetric approach or the parametric method (Slottje, 1990).

[15] In the income inequality literature, there is evidence that ignorance about intra-household inequality biases inequality measures downwards significantly, but that these biases have negligible impact on cross-sectional comparisons (Haddad and Kanbur, 1990). However, evidence on the co-location of firms at the micro-geographic level points to the importance of narrowly confined clusters. According to Duranton and Overman (2002), the relevant distance for geographical clusters of British manufacturing firms is mostly smaller than 50 kilometers. In comparison, the radius of a circle with a surface corresponding to the average area of regions in our data set 1 (15,000 km^2) is 69 kilometres. The degree of accuracy with which regional data reflect patterns and changes in these fundamental distributions remains to be studied systematically.

2.3 A bootstrap test for the significance of changes in geographic concentration

Any concentration index describes the dispersion of a distribution through a scalar, and it therefore has its own sampling distribution. Traditionally, inference on inequality measures has been based on asymptotic results obtained through the delta method. For a test of the equality of two distributions on the same units at different times, however, this method requires cumbersome covariance calculations to take account of the intertemporal dependencies in the data. Furthermore, the finite-sample properties of such tests are unknown.

Hence, Biewen (2001) and Mills and Zandvakili (1997) have argued in favour of using bootstrap inference. With this approach, the sampling distribution of an inequality index is estimated by multiple random resampling with replacement from the data set at hand. Through the bootstrap one can account for dependencies in the data without having to estimate covariance matrices explicitly. Biewen (2001) proved that the bootstrap test for inequality changes over time is consistent for any inequality statistic that can be expressed in terms of population moments - which includes the GE class of indices but not the Gini index. This result is shown by Biewen to be valid also for grouped data (i.e. for observed units that are aggregates of basic units). Using Monte Carlo simulations, he demonstrated that this approach achieves a finite-sample coverage accuracy that is equivalent to that obtained through analytically derived (but asymptotic) tests. Mills and Zandvakili (1997) found that the bootstrap estimated standard errors were closer to the corresponding asymptotic estimates for the Theil index than for the Gini index, and they too therefore preferred the entropy measure.

The standard use of the bootstrap is as a method for making probabilistic statements about population parameters based on a data sample drawn randomly from that population. One interpretation of this test in our context is therefore to consider our yearly sets of regional observations as random draws from the universe of (industrialised) world regions. Alternatively, one could consider the set of Western European regions as the population, and search for specifically Western European parameters. In this setting, bootstrap inference remains useful, considering that the data are measured with error, and that the measurement error is distributed stochastically across observations (assuming that measurement errors are distributed independently from y). The principal attraction of the bootstrap in this case is that it absolves us from making assumptions on the form of the measurement error distribution across observations.[16]

[16] An alternative strategy for inference on concentration indices in exhaustive samples of grouped data with measurement error is to assume certain distributions of those measurement errors and to simulate corresponding distributions for the concentration indices (Bourguignon and Morrison, 2002). That approach, however, requires strong assumptions on the distributional forms of measurement errors.

By treating all observations equally in the resampling process, the standard bootstrap method implies that the measurement errors attached with each observation are *iid* draws from the population error distribution. This assumption is difficult to justify in the context of our study, as we have strong reason to believe that measurement errors are to a large extent country-specific (i.e. spatially autocorrelated). We therefore apply block-wise resampling, defining countries as blocks. For each replication, a sample is drawn randomly among K blocks of regions, where each block has sample size R_k. Since we have no priors on the distribution of measurement errors across countries, we attach equal probability weights to those K sets of observations in the resampling procedure.[17] All bootstrap results are based on 10,000 replications.

2.4 Data

We draw on two complementary data sets, both of which are described in detail in Appendix 1. Data set 1, compiled by Cambridge Econometrics, provides a balanced panel of sectoral employment for 17 West European countries, the 15 EU member states plus Norway and Switzerland (collectively referred to as WE17). Except for Luxembourg, all country data are disaggregated into NUTS-2 or NUTS-3 regions, giving a total of 236 region-level observations per sector and year. The number of regions within countries ranges from 2 (Ireland) to 37 (UK). Employment is reported for eight sectors, covering the full range of economic activities, over the period 1975-2000.

Figure 1 illustrates the evolution over our sample period of the relative sizes of the eight sectors in data set 1. It emerges clearly that the WE17 economies have been marked in the last quarter century by pronounced growth in the relative sizes of the tertiary sector, at the expense of the primary and the secondary sectors. This fact alone provides strong motivation for studying geographic specialisation patterns not just for manufacturing industries, but across the full spectrum of economic activities.

Data set 2, compiled by Hallet (2000), reports gross value-added (GVA) of nine manufacturing sectors across the 15 EU member states (referred to as EU15). For eight countries, the data are disaggregated into either NUTS-1 or NUTS-2 regions, giving a total of 109 regions. The remaining seven countries appear in the data as single regions. Among the countries that are subdivided, the number of regions ranges from 5 (Portugal) to 23 (UK). The period covered is 1980-1995.

The two data sets differ in terms of geographic and sectoral disaggregation, but they are complementary. The time span of the second is encompassed by that of the first. Moreover, data set 1 offers a broader base for comparison of agglomera-

[17] We ran all tests also with region-level resampling. As expected, this yielded generally tighter confidence intervals, but the higher moments of the distributions underlying those intervals were not affected significantly.

tion between and within countries, because it is more regionally disaggregated. We consider employment data as preferable to data based on production values, because the former are not subject to the problems associated with price conversions across countries and years. The comparative attraction of data set 2 is the detail it provides on manufacturing sectors, which facilitates comparisons with previous research findings by bringing us closer to the data sets that have been used in most existing studies.

We complement those data sets with a vector of "peripherality indices" for our sample regions, as computed by Copus (1999). These indices range from 0 (most central region) to 100 (most peripheral region) and are derived from inversely distance-weighted averages of regional GDPs.[18] The underlying interregional distances were quantified on the basis of a regional matrix of road-freight travel times, and GDPs are measured in a common currency using purchasing-power parity exchange rates.

3 Geographic concentration: Regions versus countries

3.1 Relative concentration across all regions

3.1.1 All sectors

Sectoral Theil indices of relative concentration across the full spectrum of activities in WE17 regions (i.e. using data set 1) are reported in Table 1 and Figure 2. These indices are computed according to equation (7) using total regional employment as the weighting variable n_r.

On average over our sample period, agriculture turns out to be by far the most concentrated sector (note the log scale of Figure 2), and manufacturing is second-most concentrated, while construction is the most dispersed.

These results seem plausible. In view of the regional and sectoral aggregation problems, however, and given our research interests, our analysis focuses not on levels but on changes over time. In Table 1, we report changes in relative concentration (i) over our entire sample period 1975-2000, (ii) over the subperiod 1975-1987 and (iii) over the subperiod 1987-2000. The sample period is divided in this way since 1987 coincides with the entry into force of the Single European Act and thus the launch of the EU's Single Market programme. Hence, one can interpret the second subperiod as a time of particularly strong policy-led integration. Table 1 also reports statistical significance levels according to the bootstrap test described

[18] See equation (9) below. The regional breakdown used by Copus (1999) is in most cases finer than that of our study. Hence, we aggregated up peripherality indices of sub-regions using GDP weights. In our data set, the region with the lowest peripherality index is Inner London (21), and the one with the highest index is Northern Norway (100).

above.

We find that manufacturing is the only sector that has seen a monotonic and statistically significant increase in relative concentration. This increase was more pronounced in the post-Single Market subperiod than in the earlier subperiod. Our analysis therefore confirms the general finding of the previous literature that European manufacturing is becoming more geographically concentrated, particularly since the inception of the Single Market programme.[19]

Our results of Table 1 furthermore show that, with the exception of the "transport and communications" industry, which has become significantly more dispersed, no service sector exhibits a statistically significant change in relative concentration over the full sample period. On the whole, therefore, the evidence does not support the view of strong sectoral reallocation trends across the spectrum of economic activities. Looking at the subperiods, however, we find that the tendency to concentrate (disperse) geographically is stronger (weaker) in the second subperiod than in the first subperiod for all eight sectors. This finding is consistent with the view that the deepening of European integration through the Single Market programme has favoured geographic concentration forces.

3.1.2 Manufacturing

In Table 2, we report indices of relative concentration for disaggregated manufacturing sectors across EU15 regions, calculated from our data set 2. As noted above, these findings are not strictly comparable with those based on data set 1, due to differences of measurement units (value added instead of employment) and to narrower regional and time coverage.

The results of the two data sets are consistent in so far as they both show a trend towards stronger relative concentration of total manufacturing for the first subperiod (although not for the second one). The strongest increase in relative concentration is found for the textiles, clothing and footwear sector - a tendency which is particularly pronounced in the post-1987 subperiod but statistically significant throughout. This confirms earlier findings whereby the strongest relocation tendencies in European manufacturing are in relatively low-tech and labour-intensive sectors. We do not find a statistically significant change in the concentration index over the full 1980-1995 period for any other manufacturing sector. Six of the nine sectors display stronger concentration trends post-1987 than pre-1987.[20] Here too, we can therefore retain

[19] We estimate the association between EU membership and geographic concentration trends explicitly in Section 4.

[20] For "machinery, electrical and electronics", the largest of our nine manufacturing industries, our calculations suggest that relative concentration increased pre-1987 and decreased thereafter. Both these changes are statistically significant. Inspection of the data suggests the post-1987 decrease is primarily driven by a drop in reported value added of this sector in the West German regions. Given the estimated nature of the statistics for Germany in our data set 2, this result might be influenced by measurement problems (see Hallet, 2000).

as a stylised fact that EU industries exhibit weak overall concentration pressures, with some evidence of a strengthening subsequent to 1987.

3.2 Relative concentration: Between-country and within-country components

Exploiting the decomposability of entropy indices according to equation (4), we can track the evolution of the within-country and between-country components of geographic concentration.[21]

3.2.1 All sectors

Using data set 1, we have computed within-country shares of relative concentration ($GE_w(1)/GE(1)$) across all sectors. The results are reported in Figure 3.

On average, most of the concentration of service sectors is between countries rather than within countries. The opposite applies to manufacturing: within-country concentration largely dominates between-country concentration.

In terms of changes over time, the within-country share of relative concentration has fallen over our sample period for a majority of sectors. Hence, between-country concentration forces seem to have been relatively stronger than within-country concentration forces. Given that countries' internal markets were already liberalised in 1975, whereas our sample period was marked by strong between-country liberalisation, this result is in line with the view that European integration opens scope for between-country specialisation which hitherto had existed only at the within-country level.

Relative concentration of manufacturing exhibits a trend break in the early 1990s towards a re-increase in the within-country share. It thus appears that, after a period of more pronounced inter-country concentration processes, intra-country agglomeration forces have come to dominate relocation of manufacturing employment in the 1990s.

3.2.2 Manufacturing

Within-country shares of relative concentration for the manufacturing sectors, based on data set 2, are given in Figure 4. In this data set too, the within-share of relative concentration of total manufacturing shows a u-shaped time profile - declining in the 1980s but increasing since the early 1990s.

The industry that emerges with the clearest trend is textiles, clothing and footwear, which exhibits a steady decline in the within-country share of geographic concentration.

[21] In the context of relative concentration, a "factor decomposition" of total concentration is meaningless, since the concentration of total employment across regions weighted by total employment is zero.

3.3 Topographic concentration across all regions

The choice of spatial weights, which might seem an arcane technicality, turns out to be empirically important. Table 3 and Figure 5 report indices of topographic concentration, computed for data set 1. The difference compared to the relative concentration indices is most evident for agriculture. Of our eight sample sectors, agriculture exhibits the highest average level of relative concentration but the lowest level of topographic concentration. In both cases the gap separating agriculture from the most similarly concentrated sector is large. These results are of course entirely consistent. While agriculture is spread out more than the other sectors in line with total land area, it is typically concentrated in regions with low employment densities, and hence it is concentrated strongly when we condition the spatial distribution of agricultural employment by the distribution of total employment. Another difference between topographic and relative concentration is that service sectors are by far the most concentrated ones in the former case, whereas in terms of relative concentration they are less concentrated than manufacturing as well as agriculture.

Turning to the time profiles of our topographic concentration measures, Figure 5 suggests that the topographic concentration of total employment has remained stable over the sample period, and the bootstrap test does not reject the null hypothesis of identical concentration indices in the base and end periods.

The evident stability in the topographic distribution of total employment, however, masks offsetting changes in the topographic concentration of individual sectors. The most pronounced trends are an increase in topographic concentration of agriculture and a simultaneous decrease in the concentration of manufacturing. These changes are statistically significant. The decrease in topographic concentration of manufacturing, together with the detected increase in relative concentration, suggests that manufacturing has relocated from regions with high employment density to regions with low employment density.

3.4 Topographic concentration: Decompositions

3.4.1 Between-country and within-country components

The decomposition of aggregate topographic concentration into its within-country and between-country components is reported in Figure 6. On average, service sectors have the highest share of within-country concentration, again as opposed to the patterns observed for relative concentration. Nevertheless, the two types of measures share a trend: as in the case of relative concentration, we detect a falling tendency of the within-country share for a majority of sectors. The 1990s, however, are characterised by an apparent reversal in this tendency, that is by an increase in the within-country share of topographic concentration. That reversal is most manifestly evident for the manufacturing sector.

3.4.2 Factor decomposition

In Figure 7, we report the results from a factor decomposition of the topographic concentration of total employment, based on the GE(2) index (equation (8)) and the decomposition rule of equation (6). The manufacturing sector accounted for a continuously decreasing contribution to the topographic concentration of total employment. This result is consistent with the declining share of manufacturing in total employment (Figure 1) and its decreasing topographic concentration (Figure 5) - two factors which correspond to the second and third term respectively in the "natural" decomposition rule expressed by equation (6).

The factor-decomposition analysis also shows that non-market services on average account for the largest share of total topographic concentration. Hence, public-sector employment appears as the biggest contributor to the uneven geographical spread of economic activity.

4 Centre-periphery gradients and EU membership

The measures of geographic concentration used above possess the feature called "anonymity" in the income-distribution literature. Anonymity refers to the axiom that any permutation of basic units which changes only their ordering should not affect measured inequality. In other words, no attribute of a basic unit should matter except for its level of y. In the spatial context, this implies that no account is taken of the position of basic units (and observed units) relative to each other and relative to some fixed spatial reference point. In this section, we break the spatial anonymity inherent in the analysis of the previous section by identifying regions (i) according to their market potential, and (ii) by whether or not they belong to an EU member country. All results reported in this section are calculated from our data set 1.

4.1 The importance of being central

One of the principal insights of the "new economic geography" is that a location's market access can be a powerful attractor for increasing-returns activities.[22] The policy relevance of this issue is obvious.

[22] In those models, the arrival of increasing-returns firms in a location is typically of sufficient magnitude that it increases the market potential of that location significantly and thereby triggers further arrivals of firms in a process of cumulative causation. Market access therefore becomes an endogenous variable. Our analysis abstracts from such processes by taking the market potential of regions as exogenous and time invariant. Our finding that the topographic concentration of overall employment has remained virtually unchanged over our sample period (see Figure 5) would seem to justify this restriction.

4.1.1 The regression model

We use the peripherality index calculated by Copus (1999), which corresponds to the inverse of Harris's well-known market-potential measure:

$$P_r = \left(1 - \sum_{s=1}^{R} \frac{G_s}{d_{rs}}\right) * 100, \tag{9}$$

where G_r denotes regional GDP and d_{rs} stands for the distance in terms of road-freight travel time between regions r and s. Intra-regional distances d_{rr} are defined as one third of the longer axis of a rectangle bounding that region with north-south-east-west orientation.

Based on this measure, we compute centre-periphery gradients of our sample sectors by estimating the following simple specification separately for each sector and year:

$$\ln\left(\frac{\frac{y_{rf}}{\sum_f y_{rf}}}{\frac{\sum_r y_{rf}}{\sum_f \sum_r y_{rf}}}\right)_{rft} = \alpha_{ft} + \beta_{ft} P_r + \varepsilon_{rft}, \tag{10}$$

where, as before, y is employment and f stands for sectors. In addition, t denotes years, α and β are regression coefficients, and ε is a stochastic error. Our dependent variable is the log of what is commonly referred to as a Balassa index or location quotient (Overman *et al.*, 2001). This index scales sectoral employment by total employment, and hence it belongs to the class of *relative* concentration measures. We take logs in order to make the index symmetric.

Since there is evidence of between-country heteroskedasticity, we base our inference on White-adjusted t-statistics. To assess the statistical significance of changes in $\widehat{\beta}$ between sample years, we compute F tests on the hypothesis that $\widehat{\beta}_t - \widehat{\beta}_{t-x} = 0$, using seemingly unrelated regression estimates of the disturbance covariances in order to account for cross-equation error correlation (Greene, 2000: 620).

4.1.2 Results: centre-periphery gradients in Europe

Table 4 reports our results, based on sector-level regressions for 1975, 1987 and 2000.[23] The results broadly conform with expectations based on casual observation. Agriculture is the only sector that exhibits a consistently positive and statistically significance locational bias towards peripheral regions. Conversely, three sectors are statistically significantly concentrated in central regions for all three sample years: manufacturing and energy, banking and insurance, and "other market services".

Looking at changes over time, we find that "other market services" is the only sector that exhibits a significant increase over the sample period in its tendency

[23] Plots of the regional Balassa indices against the peripherality index for the year 2000 are given in Appendix 2.

to concentrate at the centre. Conversely, three sectors have relocated significantly towards peripheral regions: manufacturing, construction and non-market services.

In the previous section we saw that the geographic distribution of manufacturing employment, conditioned on the distribution of total employment, has become tighter, while, conditioned on physical area, it has become more dispersed. Here we find that the centre-periphery dimension has lost some of its importance in shaping this distribution. We therefore conclude that manufacturing activity has been relocating away from high-density central regions.

4.2 The importance of being an EU member

One issue of particular interest from a policy perspective is the impact of EU integration on geographic concentration patterns. Exploiting the richness of our data set in terms of time coverage and intra-country information, we explore two questions: was accession to the EU associated with a change in the time profile of geographic concentration within countries? and: was accession to the EU associated with a change in the time profile of sectoral centre-periphery location trends?

4.2.1 The regression model

We estimate the following regression model separately for each sector:

$$\mathbf{Z} = \mathbf{I}\boldsymbol{\alpha} + \mathbf{T}\boldsymbol{\beta} + \mathbf{E}\gamma + \boldsymbol{\epsilon}, \tag{11}$$

where

- K denotes the number of sample countries and T the number of sample years,
- $\mathbf{Z}$ is a $KT \times 1$ vector either of
  - within-country Theil indices of relative concentration, or of
  - estimated within-country centre-periphery gradients $\hat{\beta}$ from equation (10), regressed country-by-country;[24]
- $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are $K \times 1$ vectors of regression coefficients
- $\mathbf{I}$ is a $KT \times K$ matrix that consists of K diagonally stacked $T \times 1$ vectors of 1s, and zeros elsewhere;
- $\mathbf{T}$ is a $KT \times K$ vector consisting of K diagonally stacked $T \times 1$ vectors of sample years in ascending order ([1975, 1976,...,2000]) and zeros elsewhere;

[24] Plots of the estimated within-country $\hat{\beta}$s are given in Appendix 3.

- $\mathbf{E}$ is a $KT \times 1$ vector whose values are equal to the number of years either since the relevant country's accession to the EU or since 1975, whichever of the two is more recent, and zero for non-EU country-years;[25]
- γ is a regression coefficient (1×1); and
- $\boldsymbol{\epsilon}$ is a $KT \times 1$ vector of stochastic disturbances.

This is a piecewise linear spline function. The main object of our interest is γ, a slope shifter contingent on accession to the EU.

In order to estimate equation (11), we need to take account of some dependencies in the data. Specifically, inspection of the data reveals significant intra-country autocorrelation and cross-country error correlation. Since the number of panels is relatively small ($K = 17$), we follow Beck and Katz (1995) and estimate the coefficients with feasible generalised least squares accounting for the intra-country autocorrelation (Prais-Winsten method) whilst taking account of the cross-country correlation and implied heteroskedasticity by basing inference on panel-corrected standard errors.

4.2.2 Accession to the EU and intra-country geographic concentration

The estimation results for the model with $\mathbf{Z}$ defined as within-country indices of relative concentration are reported in Table 5. For presentational reasons, we report only $\hat{\boldsymbol{\alpha}}$ and $\hat{\gamma}$.[26] Our model accounts for between 74% and 99% of the variance in the dependent variable. Accession to the EU has significantly affected within-country geographic concentration in three sectors: manufacturing, market services and non-market services. In all of these cases, EU accession has increased the slope of within-country concentration relative to time, hence, EU membership has been associated with increasing intra-country concentration of those three sectors. The within-country concentration of agriculture and construction, however, has not been affected by accession to the EU in a statistically significant way.

4.2.3 Accession to the EU and intra-country centre-periphery gradients

The results of the same exercise but with $\mathbf{Z}$ defined as estimated within-country centre-periphery gradients are reported in Table 6.[27] Again, our model accounts for most of the sample variance in the dependent variable, between 47% and 99%.

[25] We have experimented with alternative definitions of this varible, by starting the counter one or two years ahead of countries' accession dates, in order to take account of anticipatory relocation decisions. This made no qualitative difference to our results. The results are available upon request.

[26] In this section, we have amalgamated the market-services sectors into a single sector. Luxemburg had to be dropped from the data set, because for the intra-country concentration index to be computable, at least two regions are needed.

[27] Luxemburg and Ireland had to be dropped from the data set, because for the intra-country $\widehat{\beta}$ to be computable, at least three regions are needed.

The coefficient on the slope-shifting EU-accession variable is statistically significant in two sectors: manufacturing and market services. Accession to the EU is associated with an increasing tendency for manufacturing activity to locate in countries' peripheral regions. The opposite appears for market services, where EU accession is associated with an increasing tendency towards location in central regions.

5 Theoretical Interpretation

Our empirical characterisation of geographic concentration patterns is not explicitly rooted in a specific theoretical framework, but it lends itself to some meaningful interpretation against the background of trade and location theory.

We will focus here on our decompositions of concentration changes into between-country and within-country components. In theory, the distinction between countries and regions could be modelled in different ways, but it is standard to base it on the assumption that factors of production move more freely among regions inside a country than between countries. This assumption is empirically well founded.[28]

The theoretical question we pose is straightforward. Define regions as spatial units among which both goods and factors are mobile at lower cost than among countries, and define economic integration as a reduction in the costs of moving goods across both regional and national borders. In this setup, are integration-induced relocation patterns among regions qualitatively different from relocation patterns among countries?

For the Heckscher-Ohlin model, Mundell (1957) has established that goods trade and factor mobility are substitutes: if factors are costlessly mobile while goods are not, factors will move until relative endowments are equalised across countries, and goods trade therefore becomes redundant. If we assume that factor movements are costless among regions but costly among countries, and that some costs to goods trade persist, then this model implies that regions are less specialised than countries (i.e. not at all). Applied to regions (among which factors flow costlessly), reductions in trade barriers will have no effect on specialisation; whereas, applied to countries (among which factors cannot flow), reductions in trade barriers will increase specialisation in accordance with the Heckscher-Ohlin theorem.

Realistically, however, we want to track specialisation changes associated to product-market integration in a framework where both factor and goods trade incur some costs. Such an extension of the Mundell model has been developed by Norman and Venables (1995). They have proposed a $2\times2\times2$ Heckscher-Ohlin model with costly goods and factor trade. In that model, one can track the effects of reductions in costs of goods trade while holding constant the costs of factor trade at various

[28] Helliwell (1997), for instance, calculated that the "border effect" between Canada and the United States was of the order of 20 for merchandise trade but of the order of 100 for migration flows. For Europe, Faini (1999) shows that intra-national migration rates significantly exceed international migration rates.

levels.[29] It turns out that the intuitive extension of Mundell's result holds: when factor trade costs are relatively high, reductions in goods trade costs will reduce the incentives for factor movements and thus favour more specialised equilibria. With factor trade costs below a certain threshold, however, reductions in trade costs will no longer affect incentives for factor movements and thus have no impact on international specialisation. Accordingly, integration will trigger stronger specialisation between countries than between regions: the higher are initial costs of international factor movement, the greater will be the likelihood that trade liberalisation will increase specialisation.

Conversely, Venables (1999) has shown that, in a similar framework but with increasing returns and cumulative causation, integration may trigger stronger specialisation (termed "agglomeration" in this modelling context) if factor mobility is higher. In a new economic geography model featuring mobile firms as well as mobile labour, Puga (1999) showed that labour mobility can reinforce agglomeration economies, whereas labour immobility acts as a dispersion force once trade costs have fallen below a critical point. Essentially, agglomeration forces increase both in product-market integration and in factor-market integration. This would suggest that the scope for geographic concentration is greater within countries than between countries. Hence, a "new economic geography" framework can produce the prediction on relative within-country concentration that is diametrically opposed to the prediction arising in the neoclassical model.

These theoretical results invite speculation about our findings in Section 2. If increasing between-country concentration were indeed driven by neoclassical determinants, and an increase in the share of within-country concentration reflects geographic agglomeration forces, then we could conjecture that, up to the 1980s, neoclassical factors have dominated the relocation of European manufacturing employment, whereas agglomeration forces have come to dominate since the 1990s.

In service sectors, on the other hand, between-country concentration has generally increased relative to within-country specialisation, which, based on the reasoning given above, would indicate a predominance of neoclassical specialisation forces. Two arguments mitigate against this interpretation, however. First, for services the magnitude of the reduction of cross-border relative to intra-country transaction costs has likely been particularly large, so that even a preponderance of agglomeration-type location forces could be compatible with a falling share of within-country concentration. Second, our findings in Section 4 that market services show particularly strong and growing centre-periphery gradients, and that these gradients have been reinforced by EU integration, suggests that proximity to large markets is becoming more important for market services as trade costs fall - a typical feature of "new economic geography" models.

[29] This aspect of the model has been discussed by Venables (1999).

6 Conclusions

We have provided an account of geographic concentration patterns in a broad range of sectors across Western European regions and countries from 1975 to 2000. Geographic concentration is quantified using entropy indices. These indices present two major advantages: they are decomposable, and they lend themselves to statistical inference through bootstrap tests. We distinguish between "relative" concentration, where location patterns are expressed relative to the spatial distribution of aggregate economic activity, and "topographic" concentration, where location patterns are expressed relative to physical space. In addition, we have estimated centre-periphery gradients in sectoral location patterns and assessed the impact of countries' accession to the European Union on changes in their internal economic geography.

Our study confirms the prevailing view of a European manufacturing sector that is slowly becoming more geographically concentrated, relative to the spatial spread of total employment (but not relative to physical space). We find that this process is statistically significant. Accession to the EU has strengthened concentration tendencies inside the new member countries. However, manufacturing concentration was not biased towards centrally located regions. The tendency of manufacturing activity to locate in economically central European regions has been significantly reduced over our sample period, and accession to the EU has strengthened those centrifugal location forces inside of the countries concerned. Finally, on manufacturing, we find a non-monotonic evolution of the within-country share in total geographic concentration, with a decrease in the 1970s and 1980s and an increase in the 1990s - a result which is consistent with a recent emergence of "new economic geography"-type agglomeration forces.

Service sectors are generally less geographically concentrated than manufacturing and agriculture. Market services have been re-locating towards economically central regions, and this process seems to have been reinforced by EU integration. Conversely, non-market services became increasingly located in peripheral regions, but this tendency did not appear to be influenced by EU integration.

With respect to the policy-related motivation for distinguishing within-country from between-country concentration, as discussed in the Introduction, we find that the average share of between-country concentration in total geographic concentration has been increasing. This suggests that shocks which originate in specific industries may be increasingly translating into country-specific shocks. On the question of the optimal jurisdictional level at which to conduct regional policy, our finding would favour delegation to supranational authorities.

We hope to have shown that, using appropriate quantitative techniques and sufficiently comprehensive data sets, descriptive empirics on economic geography can be a fruitful exercise. Yet, it is in the nature of such work that further improvements are not difficult to conceive. For example, the measure of centrality/peripherality could be made time-variant and sector-specific; and for even closer correspondence to location theory, one could separately estimate a region's access to input and output markets for each industry. It could also be interesting to describe evolutions of the full distribution of sectoral location patterns including transitions over time of region-sector observations inside those distributions, and to compute measures of spatial separation so as to assess the contiguity of sectoral clusters.

The biggest constraint on the quality of research on location patterns in Europe, however, is the quality of available sub-national data. Our analysis cannot entirely escape the spatial and sectoral aggregation biases inherent in conventional regional statistics, even though we do our best to minimise their distorting impact . If it were possible to merge plant-level micro-geographic data sets that have been collected in several European countries, ideally encompassing services as well as manufacturing establishments, the description of the European economic geography could take a quantum leap in terms of accuracy, detail and inference. In the meantime, we believe that our approach helps extract maximum information from the available statistical material.

References

[1] Aiginger, Karl and Steve W. Davies (2001) Industrial specialisation and geographic concentration: Two sides of the same coin? *Working Paper #23*, University of Linz.

[2] Aiginger, Karl and Wolfgang Leitner (2002) Regional concentration in the United States and Europe: who follows whom? *Weltwirtschaftliches Archiv*, 138(4): 652-679.

[3] Aiginger, Karl and Michael Pfaffermayr (2003) The Single Market and geographic concentration in Europe. *Review of International Economics*, forthcoming.

[4] Amiti, Mary (1999) Specialisation patterns in Europe. *Weltwirtschaftliches Archiv*, 135: 573-593.

[5] Arbia, Giuseppe (1989) *Spatial data configuration in statistical analysis of regional economic and related problems.* Kluwer.

[6] Beck, Nathaniel and Jonathan N. Katz (1995) What to do (and not to do) with time-series cross-section data. *American Political Science Review*, 89(3): 634-647.

[7] Biewen, Martin (2001) Bootstrap inference for inequality, mobility and poverty measurement. *Journal of Econometrics*, 108: 317-342.

[8] Bourguignon, François (1979) Decomposable income inequality measures. *Econometrica*, 47: 901-920.

[9] Bourguignon, François and Christian Morrisson (2002) Inequality among world citizens: 1820-1992. *American Economic Review*, 92(4): 727-744.

[10] Brülhart, Marius (2001a) Evolving geographic concentration of European manufacturing industries. *Weltwirtschaftliches Archiv*, 137: 215-243.

[11] Brülhart, Marius (2001b) Growing alike or growing apart? Industrial specialisation of EU countries. In: Wyplosz, C. (ed.) *The Impact of EMU on Europe and the Developing Countries*, Oxford University Press.

[12] Clark, Todd and Eric van Wincoop (2001) Borders and business cycles. *Journal of International Economics*, 55: 59-85.

[13] Combes, Pierre-Philippe and Henry G. Overman (2003) The spatial distribution of economic activities in the European Union. In: Henderson V. and J.-F. Thisse (eds.) *Handbook of Urban and Regional Economics*, Elsevier-North Holland, Amsterdam, forthcoming.

[14] Copus, Andrew K. (1999) A new peripherality index for the NUTS III regions of the European Union. Report for the Regional Policy Directorate of the European Commission.

[15] Cowell, Frank A. (1980) On the structure of additive inequality measures. *Review of Economic Studies*, 47: 521-531.

[16] Duranton, Gilles and Henry G. Overman (2002) Testing for localisation using micro-geographic data. *CEPR Discussion Paper* #3379.

[17] Faini, Riccardo (1999) European migrants: An endangered species? In: Richard E. Baldwin et al. (eds.) *Market integration, regionalism and the global economy*, Cambridge University Press.

[18] Fujita, Masahisa; Paul Krugman and Anthony J. Venables (1999) *The spatial economy: Cities, regions and international trade*, MIT Press.

[19] Fujita, Masahisa and Jacques-François Thisse (2002) *Economics of agglomeration*, Cambridge University Press.

[20] Giannetti, Mariassunta (2002) The effects of integration on regional disparities: Convergence, divergence or both? *European Economic Review*, 46: 539-567.

[21] Greene, William H. (2000) *Econometric analysis*, 4th ed., Prentice Hall.

[22] Haaland, Jan I.; Hans J. Kind; Karen H. Midelfart Knarvik; and Johan Torstensson (1999) What determines the economic geography of Europe?" *CEPR Discussion Paper* #2072.

[23] Haddad, Lawrence and Ravi Kanbur (1990) How serious is the neglect of intra-household inequality? *Economic Journal*, 100: 866-881.

[24] Hallet, Martin (2000) Regional specialisation and concentration in the EU. European Commission Economic Papers, No. 141.

[25] Helg, Rodolfo, Paolo Manasse, Tommaso Monocelli and Riccardo Rovelli (1995) How much (a)symmetry in Europe? Evidence from industrial sectors. *European Economic Review*, 39: 1017-1041.

[26] Helliwell, John F. (1997) National borders, trade and migration. *Pacific Economic Review*, 2: 165-185.

[27] Imbs, Jean and Romain Wacziarg (2003) Stages of diversification. *American Economic Review*, forthcoming.

[28] Kalemli-Ozcan, Sebnem; Bent E. Sorensen and Oved Yosha (2003) Risk sharing and industrial specialization: regional and international evidence. *American Economic Review*, forthcoming.

[29] Krugman, Paul (1991) *Geography and Trade*. MIT Press.

[30] Midelfart Knarvik, Karen H.; Henry G. Overman; Stephen J. Redding and Anthony J. Venables (2000) The location of European industry. European Commission Economic Papers, No. 142.

[31] Mills, Jeffrey A. and Sorushe Zandvakili (1997) Statistical inference via bootstrapping for measures of inequality. *Journal of Applied Econometrics*, 12: 133-150.

[32] Mundell, Robert A. (1957) International trade and factor mobility. *American Economic Review*, 47: 321-335.

[33] Norman, Victor D. and Anthony J. Venables (1995) International trade, factor mobility and trade costs. *Economic Journal*, 105: 1488-1505.

[34] OECD (2001) *OECD territorial outlook*. Paris.

[35] Overman, Henry G.; Stephen Redding and Anthony J. Venables (2001) The economic geography of trade, production and income: a survey of empirics. *CEPR Discussion Paper* #2978.

[36] Peri, Giovanni (1998) Technological growth and economic geography. *IGIER Working Paper* #139, Bocconi University.

[37] Quah, Danny (1996) Regional convergence clusters across Europe. *European Economic Review*, 40: 951-958.

[38] Puga, Diego (1999) The rise and fall of regional inequalities. *European Economic Review*, 43: 303-334.

[39] Shorrocks, Anthony F. (1980) The class of additively decomposable inequality measures. *Econometrica*, 48: 613-625.

[40] Shorrocks, Anthony F. (1982) Inequality decomposition by factor components. *Econometrica*, 50: 193-211.

[41] Shorrocks, Anthony F. (1984) Inequality decomposition by population subgroups. *Econometrica*, 52: 1369-1385.

[42] Slottje, Daniel J. (1990) Using grouped data for constructing inequality indices: Parametric vs. nonparametric methods. *Economics Letters*, 32: 193-197.

[43] Storper, Michael; Yun-chung Chen and Fernando De Paolis (2002) Trade and the location of industries in the OECD and European Union. *Journal of Economic Geography*, 2: 73-107.

[44] Venables, Anthony J. (1999) Trade liberalisation and factor mobility: An overview. In: Riccardo Faini et al. (eds.) *Migration: The controversies and the evidence*, Cambridge University Press.

Table 1: Relative concentration of sectors, 1975-2000 [1] (employment, 236 regions)					
Sector	**Avg** $GE(\mathbf{1})^2$	$\mathbf{\Delta} GE(\mathbf{1})_{\mathbf{75-00}}$	$\mathbf{\Delta} GE(\mathbf{1})_{\mathbf{75-87}}$	$\mathbf{\Delta} GE(\mathbf{1})_{\mathbf{87-00}}$	**Share**[3]
Agriculture	0.474	0.029	0.008	0.021	0.07
Manufact., energy	0.055	0.020**	0.004	0.016**	0.24
Banking, insurance	0.053	0.004	-0.012	0.016	0.04
Non-mkt services	0.041	-0.023	-0.022	-0.001	0.22
Transport, communic.	0.036	-0.043**	-0.036**	-0.007*	0.05
Distributn	0.031	0.007	0.002	0.004	0.13
Other mkt services	0.030	-0.005	-0.008	0.003	0.16
Constructn	0.025	0.019	-0.012*	0.031**	0.07

[1] **/* denotes rejection of H0 that $\Delta GE(1) = 0$, based on bootstrap 95%/90% confidence intervals (10,000 replications)

[2] Average annual $GE(1)$ index (employment weighted) over 1975-2000 period

[3] Sector share in total employment over the full sample period

Table 2: Relative concentration of manufacturing sectors, 1980-1995 [1] (gross value added, 116 regions)					
Sector	**Avg** $GE(\mathbf{1})^2$	$\mathbf{\Delta}GE(\mathbf{1})_{\mathbf{80-95}}$	$\mathbf{\Delta}GE(\mathbf{1})_{\mathbf{80-87}}$	$\mathbf{\Delta}GE(\mathbf{1})_{\mathbf{87-95}}$	**Share**[3]
Ores, metals	0.389	-0.0555	-0.0551*	-0.0004	0.04
Textiles, cloth., footw.	0.379	0.1649**	0.0534**	0.1115**	0.08
Transport eq.	0.163	0.0196	0.0216	-0.0020	0.10
Chemicals	0.152	0.0003	0.0085	-0.0082	0.10
Non-metallic minerals	0.142	0.0171	0.0016	0.0156	0.06
Misc. manuf.	0.111	-0.0044	-0.0064	0.0020	0.09
Machinery, electronics	0.109	-0.0057	0.0180**	-0.0238**	0.31
Paper prod.	0.104	0.0098	-0.0022	0.0120	0.08
Food, drink, tobacco	0.082	0.0114	0.0026	0.0088	0.13
Tot. manuf.	*0.043*	0.0023	*0.0071***	*-0.0048*	*1.00*

[1] **/* denotes rejection of H0 that $\Delta GE(1) = 0$, based on bootstrap 95%/ 90% confidence intervals (10,000 replications)

[2] Average annual $GE(1)$ index (GVA weighted) over 1980-1995 period

[3] Sector share in total employment over the full sample period

Table 3: Topographic concentration of sectors, 1975-2000 (employment, 236 regions)		
Sector	**Avg** $GE(\mathbf{1})^1$	$\mathbf{\Delta}GE(\mathbf{1})_{\mathbf{75-00}}$ [2]
Other market services	1.039	-0.016
Transport, communication	1.028	-0.148**
Banking, insurance	1.008	-0.024
Distribution	0.938	-0.052
Non-market services	0.890	-0.140*
Manufacturing, energy	0.868	-0.161**
Construction	0.738	0.008
Agriculture	0.490	0.104**
Total employment	*0.810*	*-0.002*

[1] Average annual $GE(1)$ index (area weighted), 1975-2000

[2] **/* denotes rejection of H0 that $\Delta GE(1) = 0$, based on bootstrap 95%/90% confidence intervals (10,000 replications)

Table 4: Centre-periphery gradients, 1975-2000[1] (236 regions)					
Sector	**Year**	$\hat{\beta} * 100$	R-sq	$(F \mid H0\text{: } \hat{\beta}_t\text{-}\hat{\beta}_{t-x}\text{=}0)^2$	
				$x \in \{12, 13\}$	$x = 25$
Agriculture	*1975*	3.46**	0.29		
	1987	3.30**	0.29	3.2	
	2000	3.36**	0.27	0.1	0.1
Manufacturing, energy	*1975*	-1.05**	0.23		
	1987	-0.87**	0.17	6.5*	
	2000	-0.47**	0.05	55.7**	32.6**
Construction	*1975*	-0.19	0.01		
	1987	0.15*	0.02	12.5**	
	2000	0.36*	0.04	4.6*	18.0**
Distribution	*1975*	-0.28**	0.04		
	1987	-0.07	0.00	10.5**	
	2000	-0.16	0.01	3.8	1.7
Transport, communications	*1975*	-0.01	0.00		
	1987	-0.10	0.00	1.1	
	2000	-0.21*	0.02	5.6*	3.3
Banking, insurance	*1975*	-1.13**	0.19		
	1987	-1.09**	0.24	0.2	
	2000	-1.15**	0.20	0.5	0.1
Other market services	*1975*	-0.55**	0.10		
	1987	-0.64**	0.18	1.8	
	2000	-0.84**	0.30	13.1**	9.1**
Non-market services	*1975*	-0.27	0.01		
	1987	-0.11	0.00	7.2**	
	2000	0.30*	0.03	96.9**	50.5**

[1] see eq. (10); **/* denote stat. significance at 99%/95%, White-corrected
[2] F-statistic on Wald test of equality of $\hat{\beta}$ across years, taking account of cross-equation error covariance

Table 5: EU membership and intra-country relative concentration					
	Dependent variable = intra-country Theil index (employment, 16 countries) (reported coeff. = estimated coeff. * 100):				
Indep. vars:	**Agric.**	**Manuf.**	**Constr.**	**Mkt serv.**	**Non-mkt s.**
Fixed effect:					
B	45.3*	9.5*	5.4	24.4*	11.3*
DK	39.3*	3.6	18.3*	21.5*	21.8*
D	16.2	7.5*	7.7	22.6*	24.4*
GR	-24.3	47.5*	35.1*	35.4*	55.3*
E	3.7	20.0*	17.6*	18.0*	27.7*
F	24.2	12.2*	19.9*	24.2*	20.8*
IRL	-1.0	14.0*	17.4*	20.9*	21.0*
I	-30.4	21.5*	23.1*	22.9*	25.9*
NL	6.2	6.7	14.4*	26.5*	20.8*
A	31.9*	-2.3*	7.6*	10.5*	9.3*
P	19.1	-4.0	14.9*	57.1*	30.8*
SF	-0.7	6.5*	4.9*	9.1*	7.6*
S	21.5*	2.6	5.8*	5.4	7.6*
UK	91.5*	9.1*	16.5*	21.9*	21.6*
N	9.4	0.7	-4.1	2.9*	2.7*
CH	9.1*	-2.9*	0.6*	1.3*	0.4*
EU effect	-0.09	0.17*	0.22	0.27*	0.27*
R^2	0.99	0.99	0.74	0.86	0.98
Notes: Prais-Winsten GLS regressions with panel-corrected standard errors, assuming contemporaneous cross-panel correlation; interactions of fixed effects with year variable included but not reported; 416 obs.; * denotes 99% statistical significance.					

Table 6: EU membership and intra-country C-P gradients

	Dependent variable = $\widehat{\beta}_{ft}$ (employment, 16 countries) (reported coefficients = estimated coefficients * 100)				
Indep. vars:	**Agric.**	**Manuf.**	**Constr.**	**Mkt serv.**	**Non-mkt s.**
Fixed eff.:					
B	32.3*	4.7	13.3	-32.7*	-14.6*
DK	23.9*	2.6	14.9*	-31.6*	-13.3
D	17.8*	2.5	5.0	-28.1*	-5.6
GR	10.6	1.9	6.8	-17.8*	-3.6
E	8.9	4.9	16.0*	-17.1*	-8.1
F	8.2	4.9	16.6*	-30.4*	-8.7
I	-0.1	5.7	15.2*	-31.1*	-9.3
NL	14.9*	8.5	8.5	-32.3*	-11.1
A	14.1*	1.4	5.5*	-25.5*	-2.6
P	25.5*	13.2*	32.4*	-75.2*	-17.7*
SF	19.1*	-16.6*	11.8	-12.0*	-16.2*
S	4.0	-3.9*	7.5*	-4.2	-1.3
UK	13.0	8.3	11.9	-28.4*	-11.9
N	7.5*	-8.4*	12.1*	-2.4	-0.4
CH	11.8*	-10.3*	1.0	0.6	-8.8*
EU effect	0.02	1.3*	0.2	-0.4*	-0.1
R^2	0.99	0.98	0.72	0.83	0.47

Notes: Prais-Winsten GLS regressions with panel-corrected standard errors (see Beck and Katz, 1995); interactions of fixed effects with year variable included but not reported; 390 observ.
* denotes 99% statistical significance.

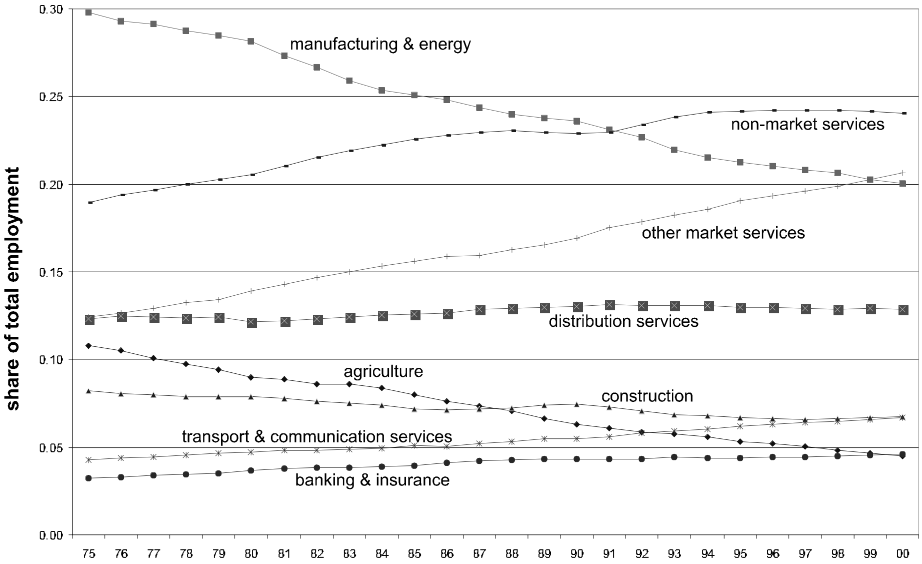


Figure 1: Sector shares in total employment, 1975-2000

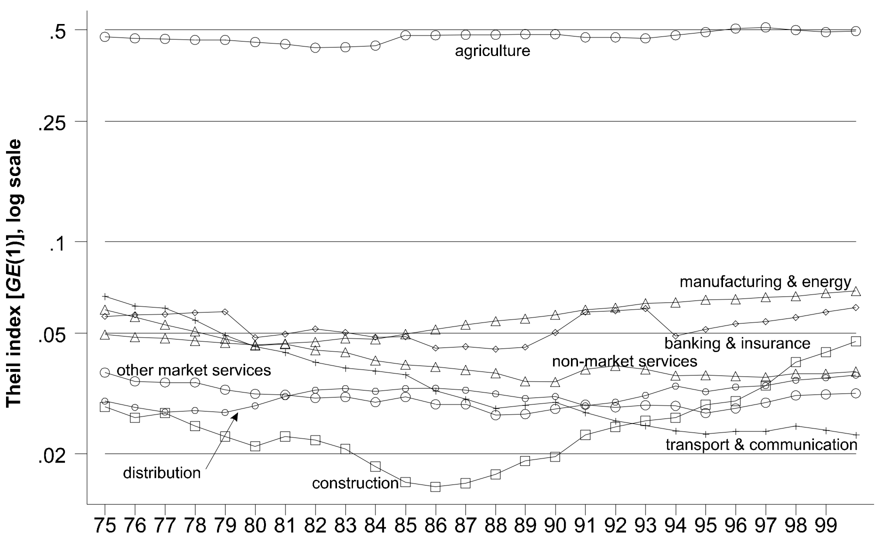


Figure 2: Relative concentration of sectors (Theil index, employment), 1975-2000

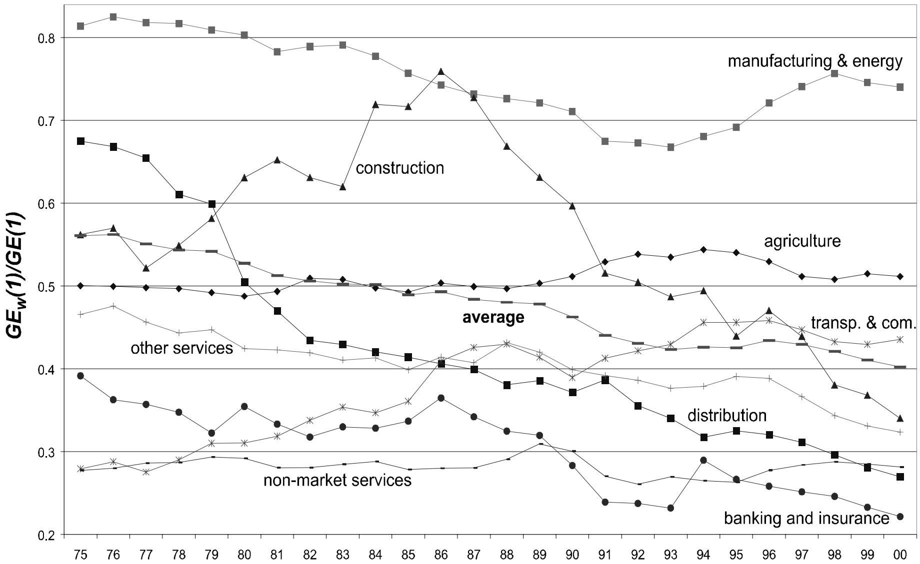


Figure 3: Within-country share in overall relative concentration (employment), 1975-2000

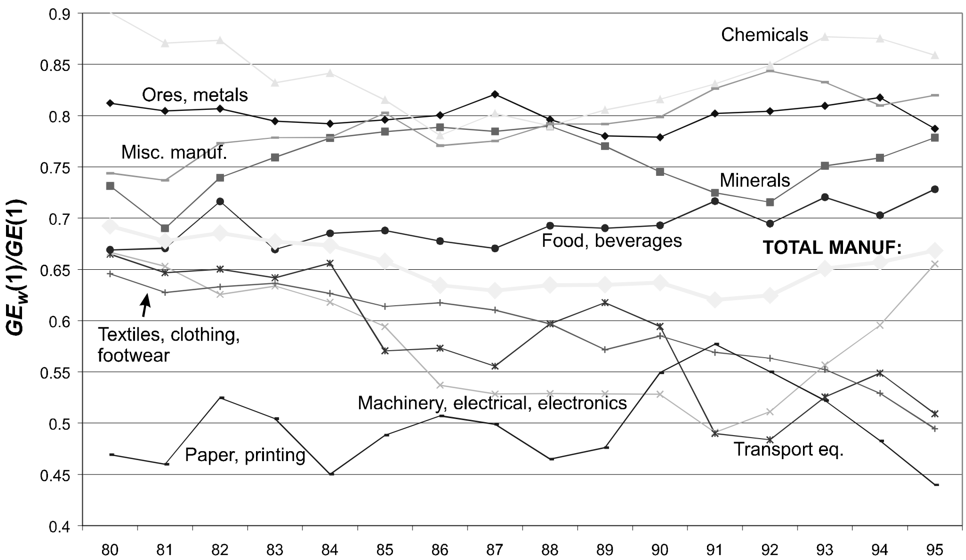


Figure 4: Within-country share in overall relative concentration of manufacturing sectors (GVA), 1980-1995

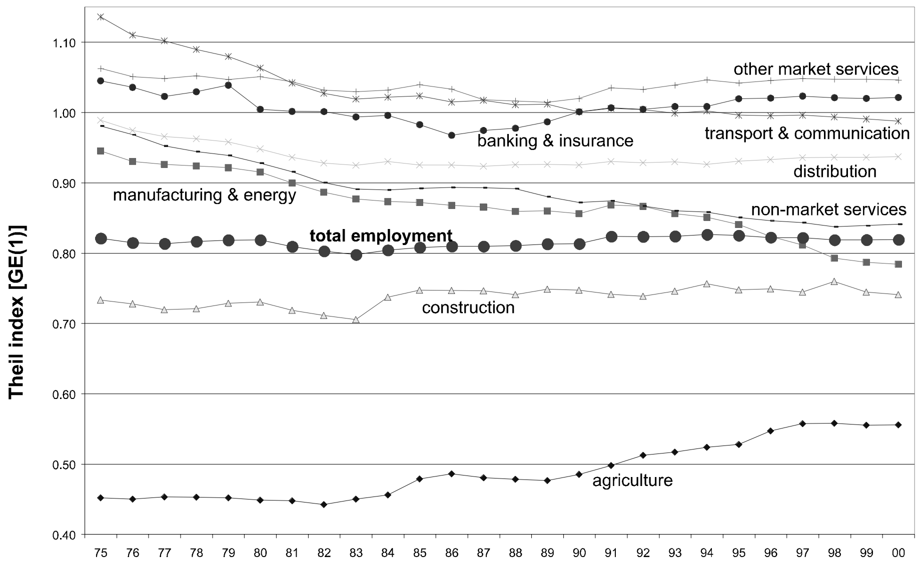


Figure 5: Topographic concentration of sectors (Theil index, employment), 1975-2000

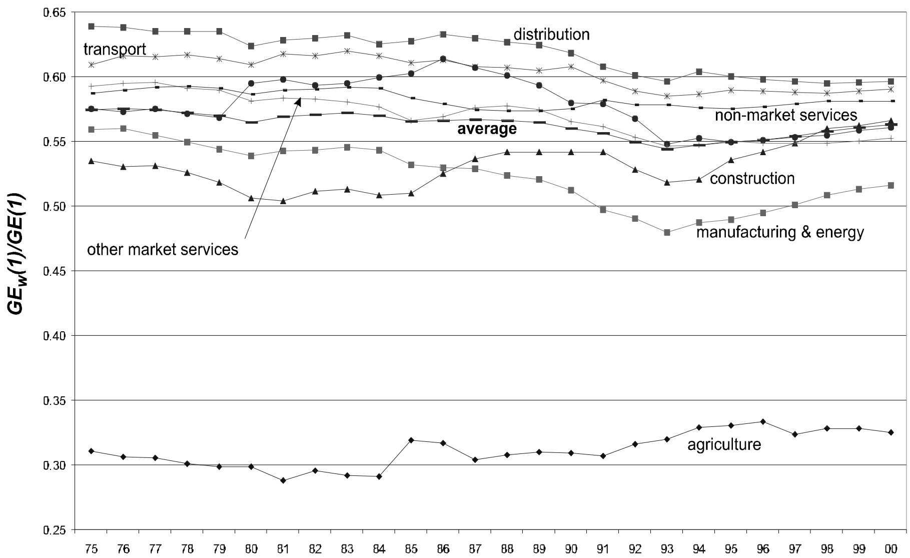


Figure 6: Within-country share in overall topographic concentration (employment), 1975-2000

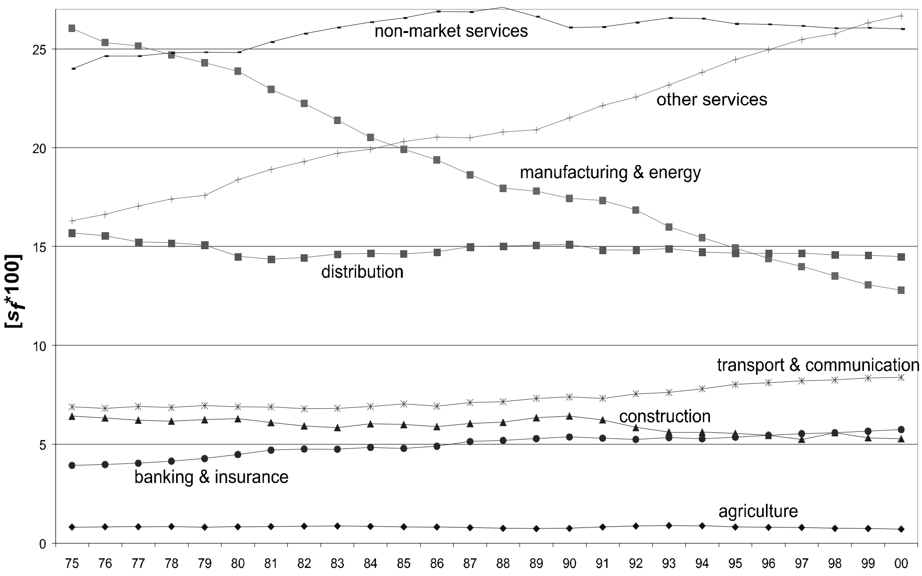


Figure 7: Sectoral "factor contributions" to topographic concentration (employment), 1975-2000

A Appendix 1: Data

A.1 Data set 1

- Source: Cambridge Econometrics Regional Database (based on Eurostat's REGIO and national sources)
- Variable: employment
- Time dimension: annual averages, 1975-2000
- Sectors: agriculture; manufacturing and energy; construction; distribution; transport and communications; banking and insurance; other market services; non-market services (8 sectors, based on NACE-CLIO classification)
- Regional breakdown: 236 regions, see Table A1
- Number of observations: 49,088

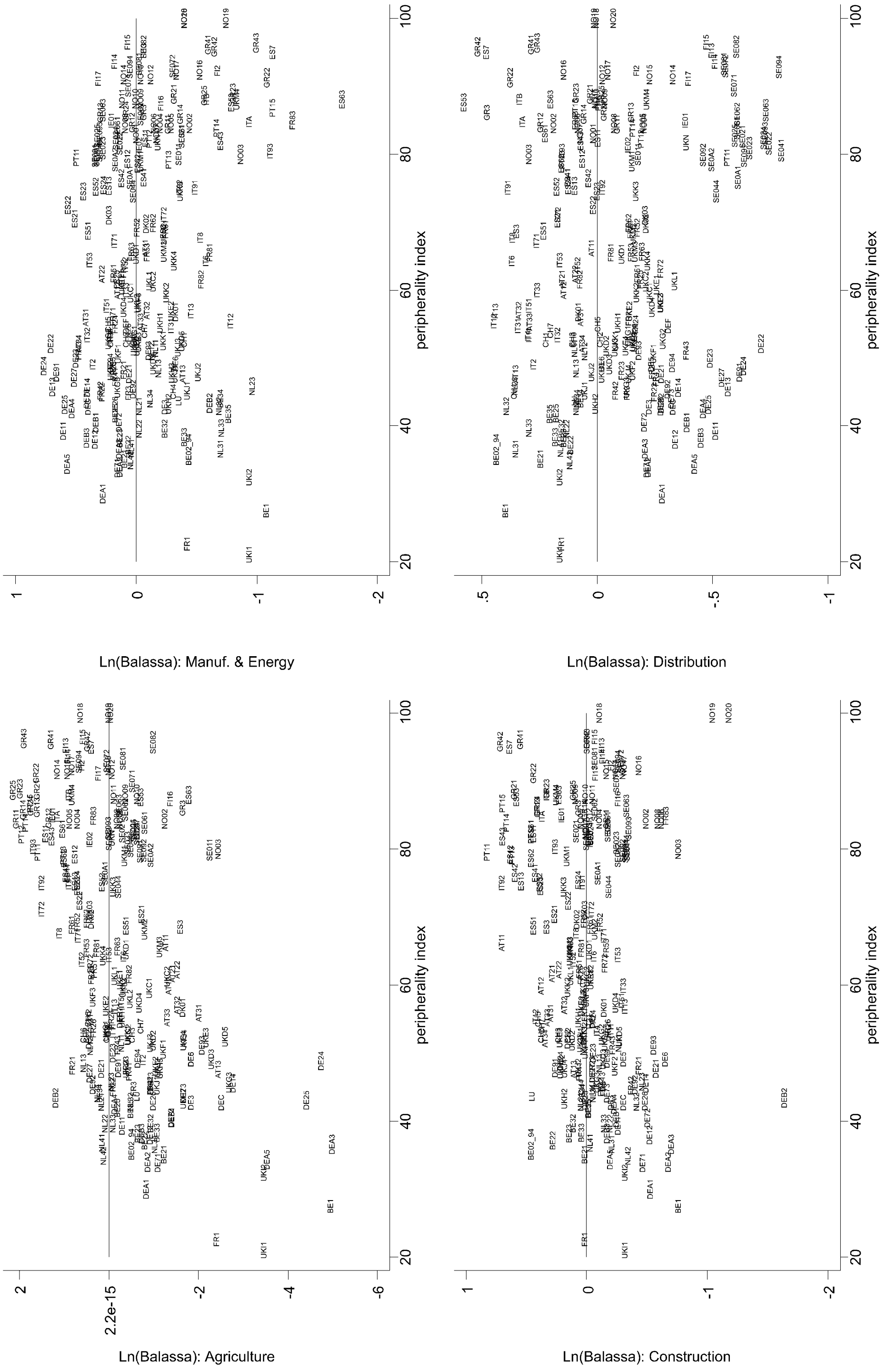
A.2 Data set 2

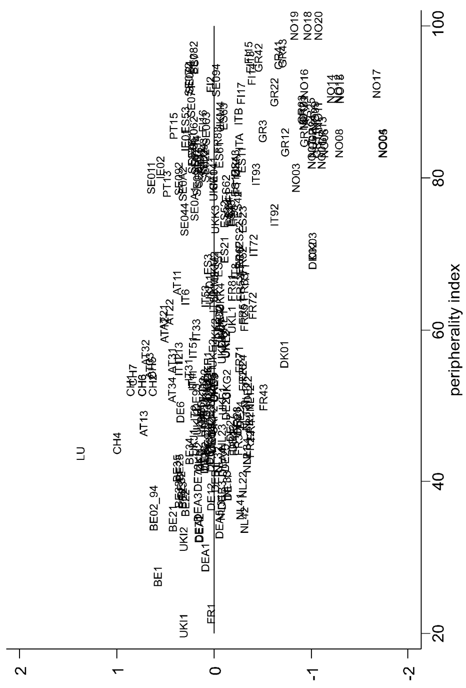
- Source: Hallet (2000) (based on Eurostat's REGIO and national sources)
- Variable: gross value added
- Time dimension: annual averages, 1980-1995
- Sectors retained: ores and metals; non-metallic minerals; chemicals; metal goods, machinery and electrical goods; transport equipment; food products; textiles, clothing and footwear; paper and printing products; misc. manufactured goods (9 industrial sectors, based on NACE-CLIO classification)
- Regional breakdown: 116 regions, see Table A1 (French "Départements d'outremer" as well as Madeira and Açores were dropped from Hallet's original data set, in order to enhance comparability with data set 1).
- Number of observations in full data set: 32,368

Data set 1					Data set 2				
Country	Number of regions for which data are available[1]	Administrative units	Classification level[2]	Observations	Country	Number of regions for which data are available[1]	Administrative units	Classification level[2]	Observations
Belgium	10	Provinces	NUTS 2	Vlaams Brabant and Brabant Wallon clustered as one region	Belgium	11	Provinces	NUTS 2	
Denmark	3	Regions	TL 2		Denmark	1			
Germany	31	Regierungsbezirke	NUTS 2	Neue Länder excluded	Germany	10	Länder	NUTS 1	Berlin and neue Länder excluded
Greece	13	Development regions	NUTS 2		Greece	1			
Spain	18	Comunidades autónomas + Ceuta y Melilla	NUTS 2		Spain	18	Comunidades autónomas + Ceuta y Melilla	NUTS 2	
France	22	Régions	NUTS 2	DOMs excluded	France	22	Régions	NUTS 2	DOMs excluded
Ireland	2	Regions	NUTS 2		Ireland	1			
Italy	20	Regioni	NUTS 2		Italy	20	Regioni	NUTS 2	
Luxembourg	1				Luxembourg	1			
Netherlands	12	Provincies	NUTS 2		Netherlands	12	Provincies	NUTS 2	
Austria	9	Bundesländer	NUTS 2		Austria	1			
Portugal	5	Comissões de coordenação regional	NUTS 2	Regiões autónomas excluded	Portugal	5	Comissões de coordenação regional	NUTS 2	Regiões autónomas excluded
Finland	6	Suuralueet	NUTS 2		Finland	1			
Sweden	21	Län	NUTS 3		Sweden	1			
United Kingdom	37	Counties or groups of unitary authorities	NUTS 2		United Kingdom	11	Government office regions	NUTS 1	According to NUTS 95 classification
Norway	19	Fylker	TL 3		Norway				
Switzerland	7	Grandes régions	TL 2		Switzerland				
TOTAL EU15	210				TOTAL EU15	116			
TOTAL WE17	236								

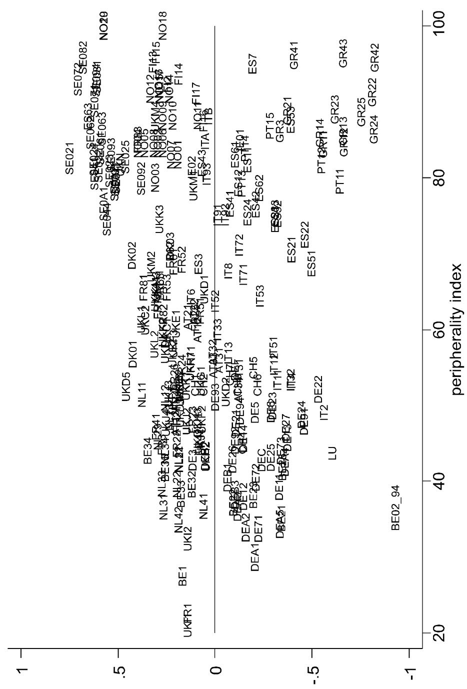
Table A1: Regional breakdown of data sets 1 and 2

B Appendix 2: Scatter plots of sectoral Balassa indices against peripherality index (year 2000)

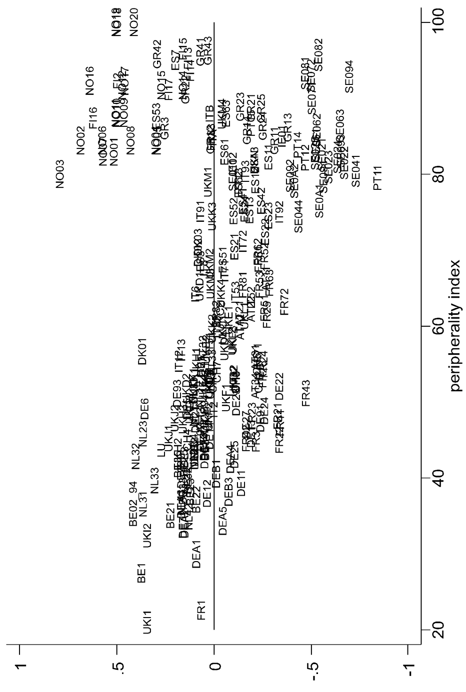




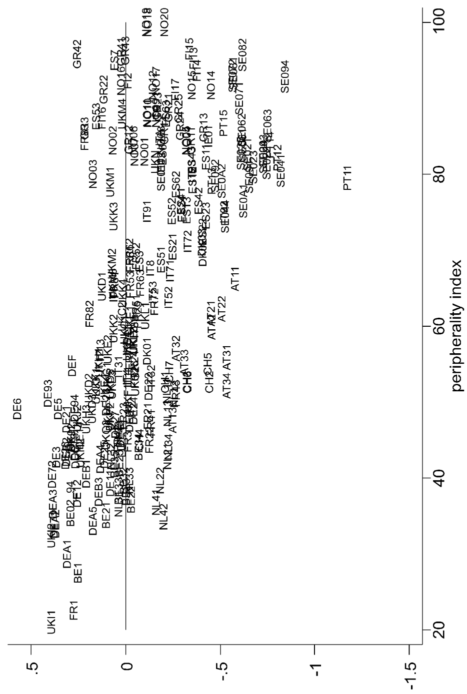
Ln(Balassa): Banking & Insurance



Ln(Balassa): Non-Mkt Services



Ln(Balassa): Transp. & Communic.



Ln(Balassa): Other Mkt Serv.

C Appendix 3: Estimated intra-country core-periphery gradients (1975-2000)